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(56) Documents cited
J. E. Hudson: "Adaptive Array Principles" (Peter Peregrinus 1981): pp. 126–7
JEE Conference Publication 180 (1979): pp. 198–202

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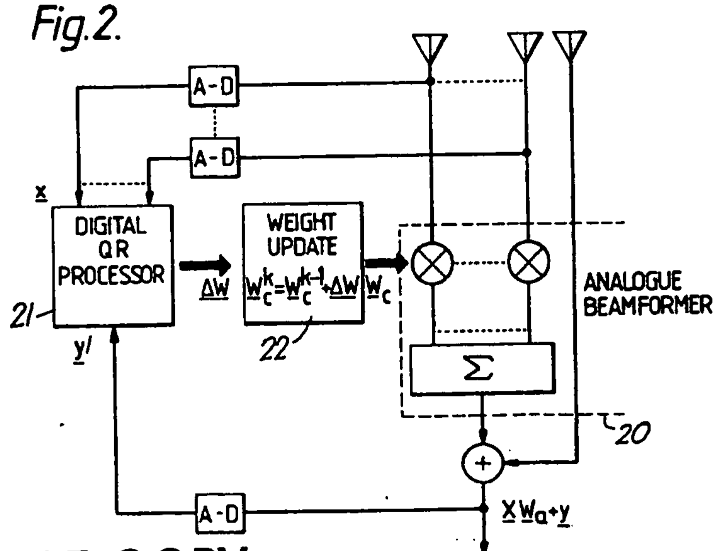
H1Q
Selected US specifications from IPC sub-class H01Q

(54) **Adaptive antenna**

(57) An adaptive antenna arrangement including a plurality of antenna elements in an array, a beam-forming network (20), one of the antenna elements providing a primary signal y(t), the remaining elements providing auxiliary signal inputs x(t) to the beam-forming network, a beam pattern controller (21) to which the auxiliary signals are applied, the controller being adapted to form amplitude and phase weights to be supplied to the beam-forming network whereby the array beam pattern is continuously adjusted to contain nulls which track the bearings of unwanted received signals, and means for combining the output of the beam-forming network with the primary signal, characterised in that the controller performs a so-called Q–R decomposition of the auxiliary signals to determine the weights to be applied to the beam-forming network and the array residual signal e(t) is fed back to the controller to modify the weights to correct for weight non-linearity in the beam-forming network.

Fig.2.



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SPECIFICATION

Adaptive antenna

This invention relates to an accelerated convergence adaptive antenna.

The objective of an adaptive antenna is to select a set of amplitude and phase weights with which to combine the outputs from the elements in an array so as to produce a far-field pattern that, in some sense, optimizes the reception of a desired signal. The substantial improvements in system anti-jam performance offered by this form of array processing has meant that it is now becoming an essential requirement for many military radar, communications and navigation systems.

The key components of an adaptive antenna system are illustrated in Fig. 1. The amplitude and phase weights are selected by a beam-pattern controller 10 that continuously updates them in respond to the element outputs. The resulting array beam pattern is continuously adjusted to contain nulls which track the bearings of any interference and jamming sources.

In the illustration, the inputs to the adaptive combiner 11 take the form of a primary (or reference) channel and a set of auxiliary signals. Usually, some facet of the desired signal is utilized to ensure that the primary input contains signals predominantly from this source. In addition, the auxiliary channel signals are arranged to provide spatial samples of the jamming and noise environment only. The multiple channel signals are then combined in order to minimize the resulting signal power at the beamformed output. Given that the combined signal is expressed by

$$e(t)=\underline{W}^{T}\underline{x}(t)+y(t) \qquad (1)$$

where $\underline{W}$ is the weight vector and $\underline{x}(y)$ and $y(t)$ describe the complex baseband envelope of the signals at the auxiliary and reference inputs to the combiner, then the residue output power is given by:

$$P_{o}=\frac{1}{2}E\{e^{*}(t)\ e(t)\}=\frac{1}{2}E\{(\underline{W}^{T}\underline{x}(t)+y(t))^{*}\ (\underline{W}^{T}\underline{x}(t)+y(t))\} \qquad (2)$$

The operator $E\{.\}$ denotes the expectation function.

The minimum output power condition can be calculated by equating the complex gradient of this expression to zero. This procedure yields for the solution for $\underline{W}$

$$\underline{W}=[E\{\underline{x}^{*}(t)\underline{x}^{T}(t)\}]^{-1}E\{x^{*}(t)\ y(t)\} \qquad (3)$$

In this expression, the first factor represents the covariance matrix associated with the signals received on the auxiliary channels. The second factor is a column vector representing the zero time lag correlations between signals received by the auxiliary and reference channels.

The most commonly employed technique for deriving the adaptive weight vector uses a "closed loop" gradient descent algorithm where the weight updates are derived from estimates of the correlation between the signal in each channel and the summed output of the array. With the closed loop scheme the summed output from the combiner is used essentially as a feedback term to the beam-pattern controller. It is this feature which allows the adaptive control algorithm to correct for weight non-linearities and offsets. The closed loop processor can be implemented in an analogue fashion using RF correlation loops or digitally in the form of the Widrow LMS algorithm.

The value of this approach should not be underestimated. Gradient descent algorithms are very cost-effective and extremely robust but unfortunately they are not suitable for all applications. The major problem with an adaptive beamformer based on a steepest gradient descent process is one of poor convergence for a broad dynamic range, signal environment. This constitutes a fundamental limitation for many modern systems where features such as improved antenna platform dynamics (in the tactical aircraft environment, for example), sophisticated jamming threats and agile waveform structures (as produced by frequency hopped, spread spectrum formats) produce a requirement for adaptive systems having rapid convergence and high cancellation performance.

In recent years, there has been considerable interest in the application of direct solution or "open loop" techniques to adaptive antenna processing in order to accommodate these increasing demands. As distinct from the "closed loop" control processor, the open loop techniques are termed so because they do not include the sum channel signal as a potential source of feedback and hence derive the weight solution directly from the input data samples. In the context of adaptive antenna processing, these algorithms have the advantage of requiring only

limited input data to describe accurately the external environment and provide an antenna pattern capable of suppressing a wide dynamic range of jamming signals. In fact, these methods usually provide an efficient implementation of the control law described by equation (3). The concept of rapid convergence rate adaptive arrays is not new and was originally introduced in a classic paper ("Rapid Convergence Rate in Adaptive Arrays", Reed, I.S., Mallett, J.D. and Brennan, L.E., IEEE Trans., 1974, AES–10, pp 853–863). Since then many different classes of "open loop" adaptive processors have been proposed involving the use of numerical techniques such as Q–R decomposition ("Application of a Systolic Array to Adaptive Beamforming", Ward, C.R., Robson, A.J., Hargrave, P.J. and McWhirter, J.G., Proc. IEEE, Vol. 131, PE F, No. 6, Oct 1984, pp 638–645), and Gram-Schmidt orthogonalisation ("Introduction to Adaptive Arrays", Monzingo. R.A. and Miller, T.W., John Wiley & Sons). An approximation to the latter technique known as Sequential Decorrelation has also been considered for this application ("Adaptive Cancellation Agreement", McQueen, J.G., UK Patent Specification No. 1–599–035, 30 Sept 1981).

Open loop algorithms may be explained most concisely by expressing the adaptive process as a least squares minimisation problem. In fact, the least-squares algorithm defines the optimal path of adaptation and requires only minimal data to provide a null pattern which cancels jamming signals over a wide dynamic range of received power levels.

The least-squares control algorithm may be derived as follows:

Consider the simplified block diagram of the adaptive antenna shown by Fig. 1. The response from the array at time t_i is given by:

$$e(t_i)=\underline{X}^T(t_i)\,\underline{W}+y(t_1) \qquad (4)$$

Here, the complex vector $\underline{x}(t_i)$ has (N–1) components describing the complex envelope of signals received across all but one element of the array at time t_i while $y(t_i)$ describes the corresponding signal received at the clamped or reference element. The vector $\underline{W}$ describes the complex weights applied across the array.

An alternative approach to the least squares estimation problem which is particularly good in the numerical sense is that of orthogonal triangularisation, as described by Golub, G.H., "Numerical Methods for Solving Linear Least-Squares Problems," Num. Math., 1965, 7, pp 206–216. This is typified by the method known as QR decomposition which we generalise here to the complex case. An n×n unitary matrix $\underline{Q}(n)$ is generated such that

$$\underline{Q}(n)\,\underline{X}(n)=\begin{bmatrix}\underline{R}(n)\\ \hline \underline{O}\end{bmatrix} \qquad (5)$$

where R(n) is an (N–1) by (N–1) upper triangular matrix. Then, since $\underline{Q}(n)$ is unitary we have

$$E(n)=||\underline{e}(n)||=||Q(n)\underline{e}(n)||=||\begin{bmatrix}\underline{R}(n)\\ \hline O\end{bmatrix}\underline{W}(n)+\begin{bmatrix}\underline{u}(n)\\ \hline \underline{v}(n)\end{bmatrix}|| \qquad (6)$$

where

$$\underline{u}(n)=\underline{P}(n)\,\underline{y}(n) \qquad (7)$$

and

$$\underline{v}(n)=\underline{S}(n)\,\underline{y}(n) \qquad (8)$$

$\underline{P}(n)$ and $\underline{S}(n)$ are simply the matrices of dimension (N–1) by n and (n–N+1) by n respectively which partition $\underline{Q}(n)$ in the form

$$\underline{Q}(n)=\begin{bmatrix}\underline{P}(n)\\ \hline \underline{S}(n)\end{bmatrix} \qquad (9)$$

It follows that the least-squares weight vector $\underline{W}(n)$ must satisfy the equation

$$\underline{R}(n)\,\underline{W}(n)+\underline{u}(n)=\underline{O} \qquad (10)$$

and hence

$$E(n)=||\underline{v}(n)|| \qquad (11)$$

Since the matrix R(n) is upper triangular, equation (10) is relatively easy to solve. The weight vector $\underline{W}(n)$ may be derived here quite simply by a process of back-substitution. Equation (10) is also much better conditioned since the condition number of $\underline{R}(n)$ is given by

$$Cn(R(n))=Cn\ (Q(n)X(n))=Cn(X(n)) \qquad (12)$$

This property follows directly from the fact that Q(n) is unitary.

When the method of Q–R decomposition is applied to signals from an antenna array, the technique provides the basis for an efficient recursive least squares minimisation process for adaptive control. When utilized in the "off-line" mode to control a real-time beamformer, however, digital beamforming is implicit since the "off-line" processing incorporates no feedback to allow for correction of weight non-linearity.

According to the present invention there is provided an adaptive antenna arrangement including a plurality of antenna elements in an array, a beam-forming network, one of the antenna elements providing a primary signal, the remaining elements providing auxiliary signal inputs to the beam-forming network, a beam pattern controller to which the auxiliary signals are applied, the controller being adapted to form amplitude and phase weights to be applied to the beam-forming network whereby the array beam pattern is continuously adjusted to contain nulls which track the bearings of unwanted received signals, and means for combining the output of the beam-forming network with the primary signal, characterised in that the controller derives an optimal gradient vector by a least-squares process or an approximation to a least-squares process to update the weights which are then applied to the beam-forming network and a feedback signal being the array residual signal is applied to the controller to modify the weights to correct for weight non-linearity in the beam-forming network. A significant feature of the invention is the aspect concerning the introduction of the feedback signal into the least-squares algorithm which enables the system to correct for weight non-linearity and offsets and yet still retain a convergence performance which is comparable with an "open loop" control process.

A preferred embodiment of the invention includes means for time multiplexing the auxiliary signals whereby the beam pattern controller performs the Q–R decomposition in a timeshared mode, the auxiliary signals being processed in a cyclic manner.

Embodiments of the invention will now be described with reference to the drawings, in which:–

Figure 1 depicts key components of a known adaptive antenna arrangement (already referred to),

Figure 2 depicts the key components of an adaptive antenna arrangement utilising Q–R decomposition of the auxiliary signals with feedback of the array residual signal,

Figure 3 depicts the arrangement of Fig. 2 with reference to a modified Q–R algorithm,

Figure 4 depicts a modification of the arrangement of Fig. 2 using a timeshared Q–R processor to control an analogue beamformer, and

Figures 5–8 illustrate the results of computer simulations of the arrangement of Fig. 4.

By reorganisation of the least squares equations that define the Q–R process, an algorithm can be derived incorporating a feedback term.

At any particular stage during adaptation, the QR or equivalent process provides a computed weight set $\underline{W}_c$ to the beamformer 20. Due to non-linearities in the weighting component, this is translated by the beamformer into a vector $\underline{W}_a$ such that the output from the network is $\underline{W}_a\underline{X}$. The computed and applied weight vectors are related by:

$$\underline{W}_c=\underline{W}_a+\underline{\Delta}w \qquad (13)$$

where $\underline{\Delta}w$ is some arbitrary weight error term caused by component non-linearity. However, it is known that the least squares processor 21 derives the weight solution $\underline{W}_c$ by minimising the error residual $\underline{e}$ represented by:

$$\underline{e}=\underline{X}\,\underline{W}_c+\underline{y} \qquad (14)$$

By substituting the equation for $\underline{W}_c$ into (14) we find that:

$$\begin{aligned}\underline{e}&=\underline{X}(\underline{W}_a+\underline{\Delta}w)+\underline{y}\\&=\underline{x}\,\underline{\Delta}w+\underline{X}\,\underline{W}_a+y \qquad (15)\\&=\underline{X}\,\underline{\Delta}w+\underline{y}' \qquad (16)\end{aligned}$$

where

$$\underline{y}'=\underline{X}\,\underline{W}_a+\underline{y}$$

is a measured quantity as indicated by Fig. 2 corresponding to the output from the analogue beamformer 20. This equation shows that, by modifying the input data to the QR or equivalent process, a weight correction term can possibly be calculated which indicates the error between the digitally computed weight solution and the weight vector actually applied by the beamformer. The QR process can be used to minimise the quantity $\underline{e}^H\underline{e}$ therefore giving a solution to the redefined covariance equations:

$$(\underline{X}^H\underline{X})\,\underline{\Delta}w = -\underline{X}^H y' \qquad (17)$$

This equation suggests that an iterative procedure could be set up whereby the weight set applied to the beamformer, $\underline{W}_c$ is updated in an update network 22 by the current correction term, $\underline{\Delta}w$ and the least squares process repeated in order to converge towards a null correction (i.e. $\underline{\Delta}w=\underline{0}$). It would not be necessary for the solution to equation (14) to be computed explicitly by this method; in fact, $\underline{W}_c$ would simply be initialised to an arbitrary vector.

Now consider an adaptive antenna algorithm that seeks to minimise the output power from an n element array, subject to a fixed unit weight being applied to one of the elements as indicated by Fig. 3. If $\underline{W}_K$ denotes the weighting vector applied to the elements with variable weights, the expectation of the appropriate steepest descent weight update equation may be expressed in the form

$$\underline{W}_{K+1}=\underline{W}_K-\mu E\{r\underline{x}^*\} \qquad (18)$$

Here $E\{r\underline{x}^*\}$ is the correlation between the array output with applied weighting vector $\underline{W}_K$ and the complex conjugates of the signals at the element outputs with variable weights, the latter being instantaneously denoted by $\underline{x}$.

If we denote the output from the element with fixed weight by y, we have that

$$r=\underline{x}^T\underline{W}_K=y \qquad (19)$$

Hence

$$\underline{W}_{K+1}=\underline{W}_K-\mu[E\{\underline{x}^*\underline{x}^T\}\,\underline{W}_K+E\{y\,\underline{x}^*\}] \qquad (20)$$

Or

$$\underline{W}_{K+1}=\underline{W}_K-\mu[\underline{M}\,\underline{W}_K+E\{y\,\underline{x}^*\}] \qquad (21)$$

where

$$\underline{M}=E\{\underline{x}^*\underline{x}^T\} \qquad (22)$$

is the covariance matrix characterising the element outputs associated with the variable weights.

The steady state weighting vector, $\underline{W}_o$, is the solution of

$$\underline{M}\,\underline{W}_o+E\{y\,\underline{x}^*\}=\underline{0} \qquad (23)$$

We may therefore write the update equation in the form

$$\underline{W}_{K+1}=\underline{W}_K+\mu\underline{M}[\underline{W}_o-\underline{W}_K] \qquad (24)$$

or

$$[\underline{W}_o-\underline{W}_{K+1}]=[\underline{W}_o-\underline{W}_K]-\mu\underline{M}[\underline{W}_o-\underline{W}_K] \qquad (25)$$

Let

$$\Delta\underline{W}_K+\underline{W}_o-\underline{W}_K$$

denote the error from the steady state weighting vector after the K^{th} update. We then have that

$$\Delta\underline{W}_{K+1}=\Delta\underline{W}_K-\mu\underline{M}\Delta\underline{W}_K \qquad (26)$$

Convergence is now seen to depend on the eigenstructure of the covariance matrix $\underline{M}$. If we modify the update equation by pre-multiplying the correlation $E\{y\underline{x}^*\}$ by $\underline{M}^{-1}$ such that

$$\underline{W}_{K+1}=\underline{W}_K-\underline{M}^{-1}\,E\{\underline{rx}^*\} \qquad (27)$$

the corresponding update equation for the weight error takes the form

$$\Delta\underline{W}_{K+1}=\Delta\underline{W}_K-\mu\Delta\underline{W}_K$$
$$=[1-\mu]\,\Delta\underline{W}_K \qquad (28)$$

Convergence is now independent of the eigenstructure of $\underline{M}$, and will occur provided $|1-\mu|<1$, corresponding to $\mu<2$ for positive μ.

This form of the accelerated convergence update equation is exactly equivalent to that derived normally for the more general case of power minimisation subject to an arbitrary linear constraint. The fact that we are dealing with a single fixed weight has enabled the equations to be recouched in a form obviating the need to evaluate the pseudoinverse of a matrix.

It is clear from the above equations that

$$\underline{M}\Delta\underline{W}_K=-E\{\underline{rx}^*\} \qquad (29)$$

Hence

$$\Delta\underline{W}_K=-M^{-1}E\{\underline{rx}^*\} \qquad (30)$$

Premultiplying the correlation $E\{\underline{rx}^*\}$ by $\underline{M}^{-1}$ to accelerate convergence is thus equivalent to calculating the weight error after the K^{th} weight update.

We now consider the method of "QR with feedback" and demonstrate how this technique produces an extremely effective implementation of the defined accelerated convergence algorithm.

Referring to Fig. 3 we have for the summed output from the array,

$$\underline{r}=\underline{X}\,\underline{W}_K+y \qquad (31)$$

where $\underline{X}$ represents a block of p data snapshots received across the weighted elements, $\underline{y}$ contains the corresponding p samples of the signal received at the clamped element, $\underline{W}_K$ is the weight set applied at the K^{th} iteration and $\underline{r}$ is the vector of the p residual components.

Following the analysis given previously, the weight update, $\Delta\underline{W}_K$ to be computed at the K^{th} iteration is obtained by minimising the norm of the residual vector, $\underline{e}$ where

$$\underline{e}=\underline{X}\Delta\underline{W}_K+\underline{r} \qquad (32)$$

The weight update can be obtained by the QR algorithm. For instance, pre-multiplying by the unitary matrix $\underline{Q}$ gives

$$\underline{Q}\,\underline{e}=\underline{Q}\,\underline{X}\Delta\underline{W}_K+\underline{Q}\,\underline{r}$$
$$=\begin{bmatrix}\underline{R}\\ \underline{o}\end{bmatrix}\Delta\underline{W}_K+\begin{bmatrix}\underline{b}_1\\ \underline{b}_2\end{bmatrix} \qquad (33)$$

and the least-squares conditon produced when $\underline{R}\Delta W_K+\underline{b}_1$.

Having thus obtained $\Delta\underline{W}_K$, the applied weight vector is then updated according to the equation

$$\underline{W}_{K+1}=\underline{W}_K+\mu\Delta\underline{W}_K \qquad (34)$$

where μ is the update gain factor. Substituting for $\Delta\underline{W}_K$ gives:

$$\underline{W}_{K+1}=\underline{W}_K-\mu\underline{R}^{-1}\underline{b}_1 \qquad (35)$$

Now, the block estimate of the covariance matrix formed from p signal samples received by the adaptively weighted elements of the array is given by $\hat{\underline{M}}$ where

$$\hat{\underline{M}}=\underline{X}^H\underline{X}=\underline{R}^H\underline{R} \qquad (36)$$

Assuming $\hat{\underline{M}}$, and its associated square root factorisation $\underline{R}$, are invertable, then

$$\underline{R}^{-1}=\hat{\underline{M}}^{-1}\underline{R}^{H} \qquad (37)$$

Therefore, substitution gives

$$\underline{W}_{K+1}=\underline{W}_{K}-\mu\underline{M}^{-1}\underline{R}^{H}\underline{b}_1 \qquad (38)$$

However, it is noted that

$$\underline{R}^{H}\underline{b}_1=\begin{bmatrix}\underline{R}\\ O\end{bmatrix}^{H}\begin{bmatrix}\underline{b}_1\\ \underline{b}_2\end{bmatrix}=\begin{bmatrix}\underline{R}\\ O\end{bmatrix}^{H}\underline{Q}\,\underline{r} \qquad (39)$$

thus giving:

$$\underline{W}_{K+1}=\underline{W}_{K}-\mu\hat{\underline{M}}^{-1}\begin{bmatrix}\underline{R}\\ \underline{o}\end{bmatrix}^{H}\underline{Q}\,\underline{r} \qquad (40)$$

However,

$$\underline{Q}\,\underline{x}=\begin{bmatrix}\underline{R}\\ \underline{O}\end{bmatrix} \text{ or } \begin{bmatrix}\underline{R}\\ \underline{O}\end{bmatrix}^{H}=\underline{X}^{H}\underline{Q}^{H} \qquad (41)$$

Therefore, we have

$$\begin{aligned}\underline{W}_{K+1}&=\underline{W}_{K}-\mu\hat{\underline{M}}^{-1}\underline{X}^{H}\underline{Q}^{H}\underline{Q}\,\underline{r}\\ &=\underline{W}_{K}\underbrace{-\mu\hat{\underline{M}}^{-1}\underline{X}^{H}\underline{r}}_{\underline{\Delta W}}\end{aligned} \qquad (42)$$

This can be compared directly with the weight update equation describing the accelerated convergence technique derived earlier where

$$\underline{W}_{K+1}=\underline{W}_{K}-\mu\underline{M}^{-1}E\{\underline{x}^{*}\,r\} \qquad (43)$$

We notice that $\underline{M}^{-1}\underline{X}^{H}\underline{r}$ is now simply the block sample estimate of $\underline{M}^{-1}E\{\underline{x}^{*}r\}$. We therefore conclude that QR with feedback implements precisely this specific form of accelerated convergence but where we have replaced the expectation operations with block estimates.

As has been discussed above, for the "Q–R with feedback" system a complete weight update was obtained by a full Q–R decomposition of at least N data vectors. Consider now "Q–R with feedback" operating in a timeshared mode. Instead of all the signal components present at the (N–1) adaptively combined channels being fed into the Q–R processor alongside the output from the analogue beamformer, the array elements are processed in a cyclic manner. A block diagram describing this process is shown by Fig. 4. Obviously, decreasing the number of inputs to the Q–R processor reduces the system complexity. The performance of such a system–in particular the effect on rate of convergence and response to several jammers with a large spread of power levels–has been assessed by computer simulation.

The simulation was of "timeshared Q–R with feedback" when used in combination with an analogue beamformer with a sinusoidal weight coefficient transfer characteristic. The program allowed cyclic rotation around the (N–1) adaptively combined elements with any number of signal components from 1 up to n–1 being taken into the Q–R processor at any one time.

Figs. 5 to 8 demonstrate the adaptive performance for a 5-element array and three independent jammers broadly separated in azimuth, of power levels 0, −10, −20 dB relative to a −70 dB noise floor at each element of the array.

In Fig. 5 the signal components from each of the adaptively combined elements are fed in turn into the Q–R processor, along with the array residue y′, to form a weight update term for that particular element. To ensure sufficient smoothing in the Q–R processor, a dwell time of 10 data samples on each element was necessary, along with an update gain factor of 0.1 to ensure stable convergence. A time constant of response of −80 samples is achieved against the strongest jammer. The rate of adaptation against the weaker jammers is considerably slower.

In Fig. 6 the size of the Q–R processor has been increased to take in the signal components from any two elements plus the array residue. The time constant of adaptation against the two

stronger jammers is now similar (time constant ~60 samples). The response against the −20 dB damming source shows an improvement over the previous example.

For the simulation shown in Fig. 7, the size of the Q–R processor now exceeds the number of independent jamming sources. The rate of adaptation against the three jammers is identical (time constant ~60 samples). Null depths in excess of 60 dB are achieved against all jammers.

Fig. 8 corresponds to a full Q–R decomposition with all (N−1) adaptively combined channels being fed into the Q–R processor alongside the array residue y′. This case is equivalent to "Q–R with feedback". Although the rate of adaptation against each jammer is identical, the null depths achieved against the jamming signals in the timescale considered, are noticeably less than the 60 dB obtained in Fig. 7.

It can be seen that the system is able to suppress jammers of a wide dynamic range of power levels providing the size of the Q–R processor is greater than the number of jammers (N_S). If fewer than N_S elements are multiplexed, then the rate of adaptation becomes power dependent. The technique is particularly interesting since, obviously, convergence performance is shown to be directly related to processor complexity. For instance, a simple processor (e.g. a two input Q–R processor) has fast convergence only for the strongest jammer; in fact, the processor is essentially performing a power normalised gradient descent algorithm. Increasing the size of the Q–R processor allows more and more jammers to be cancelled at equal rate of convergence.

It has also been shown that best cancellation performance is obtained when the Q–R processor size (i.e. the number of input channels) is one greater than the number of jammers.

CLAIMS

1. An adaptive antenna arrangement including a plurality of antenna elements in an array, a beam-forming network, one of the antenna elements providing a primary signal, the remaining elements providing auxiliary signal inputs to the beam-forming network, a beam pattern controller to which the auxiliary signals are applied, the controller being adapted to form amplitude and phase weights to be applied to the beam-forming network whereby the array beam pattern is continuously adjusted to contain nulls which track the bearings of unwanted received signals, and means for combining the output of the beam-forming network with the primary signal, characterised in that the controller derives an optimal gradient vector by a least-squares process or an approximation to a least-squares process to update the weights which are then applied to the beam-forming network and a feedback signal being the array residual signal is applied to the controller to modify the weights to correct for weight non-linearity in the beam-forming network.

2. An arrangement according to claim 1 wherein the correlation between the summed output of the array with the applied weighting and the complex conjugates of the signals at the element outputs with variable weights is premultiplied by a factor M^{-1} where M is the covariance matrix characterising the element outputs associated with the variable weights.

3. An arrangement according to claim 1 or 2 including means for time multiplexing the auxiliary signals whereby the beam pattern controller performs the least-squares process or an approximation to the least-squares process in a timeshared mode, the auxiliary signals being processed in a cyclic manner.

4. An adaptive antenna arrangement substantially as described with reference to Fig. 2, Fig. 3 or Fig. 4 of the drawings.

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Fig.1.

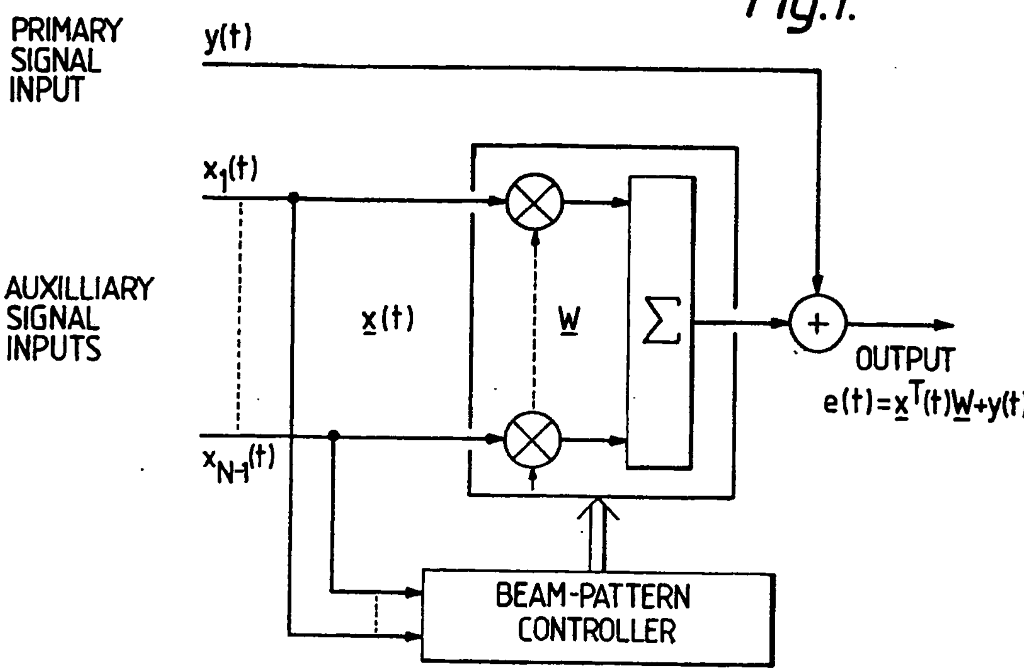
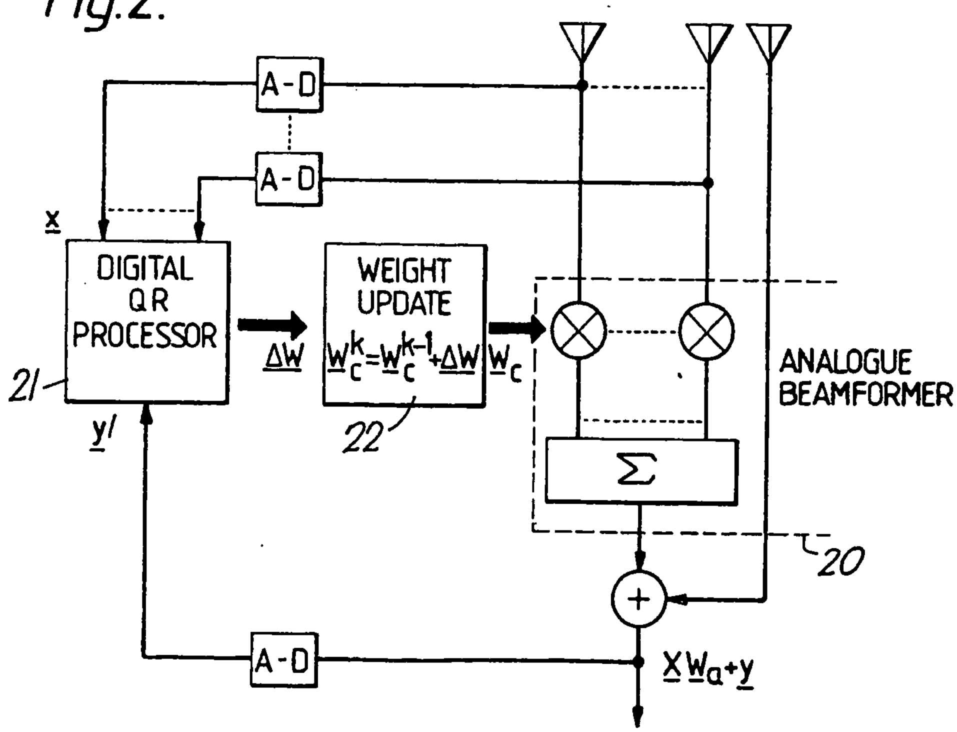

PRIMARY
SIGNAL
INPUT
y(t)
x1(t)
AUXILLIARY
SIGNAL
INPUTS
xN-1(t)
x(t)
W
Σ
+
OUTPUT
e(t)=xT(t)W+y(t)
BEAM-PATTERN
CONTROLLER

Fig.2.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WEIGHT
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Wck=Wck-1+ΔW
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Fig.3.

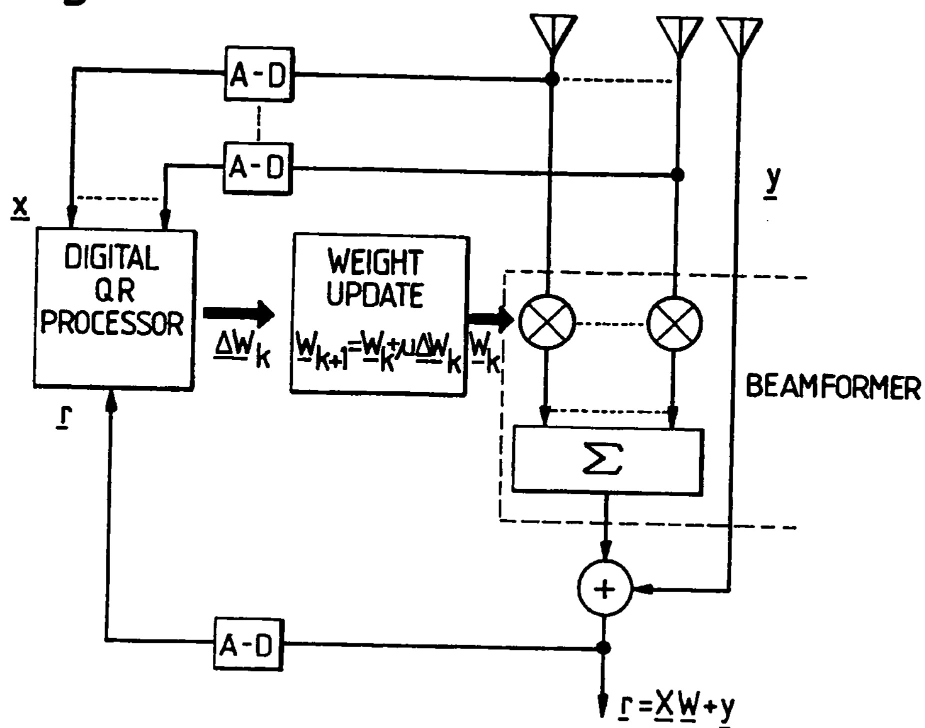
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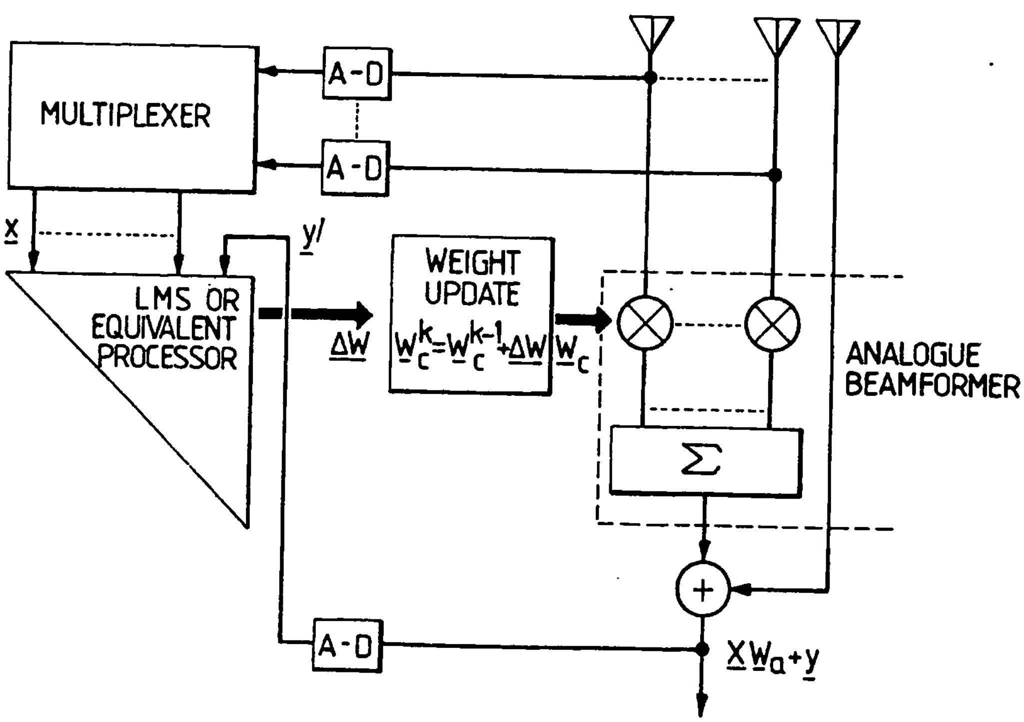
Fig.4.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W c
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2188732

COMPUTER SIMULATION DEMONSTRATING THE USE OF TIME SHARED QR WITH FEEDBACK TO CONTROL AN ANALOGUE BEAMFORMER WITH SINUSOIDAL CHARACTERISTIC

TOTAL Nº OF SAMPLES 1200
Nº OF COMPLETE WEIGHT SET UPDATES 30
Nº OF ELEMENTS PROCESSED ON EACH CLOCK CYCLE 1
DWELL TIME ON EACH ELEMENT(S) 10 SAMPLES
NUMBER OF ELEMENTS 5
ELEMENT SPACING IN WAVELENGTHS .5
NUMBER OF GAUSSIAN JAMMERS 3

JAMMER Nº 1 OF POWER 0dB AT ANGLE 25°
JAMMER Nº 2 OF POWER -10dB AT ANGLE 70°
JAMMER Nº 3 OF POWER -20dB AT ANGLE -40°
THERMAL NOISE POWER (dB) -70
SINUSOIDAL WEIGHT CHARACTERISTIC
GAIN FACTOR .1

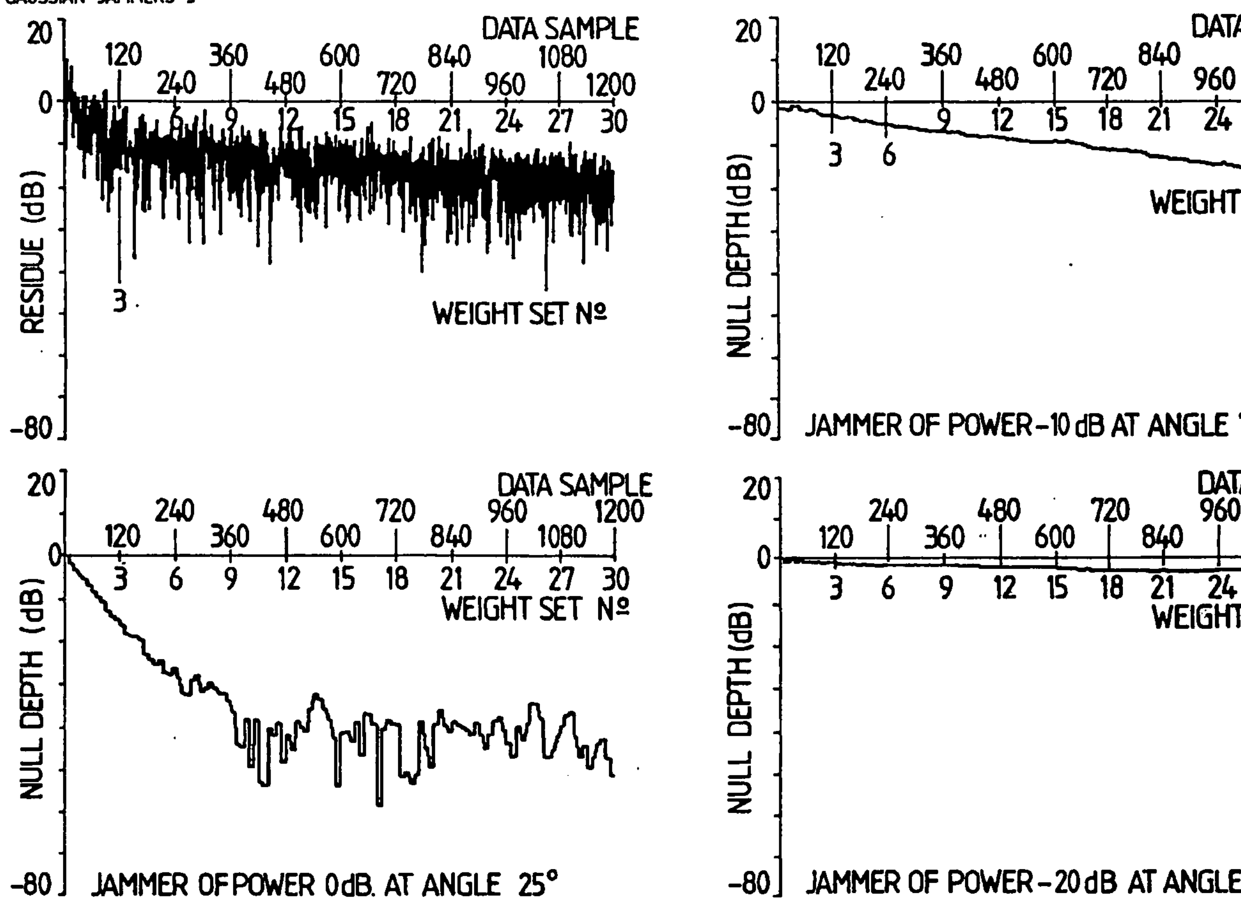

Fig.5.

COMPUTER SIMULATION DEMONSTRATING THE USE OF TIME SHARED QR WITH FEEDBACK TO CONTROL AN ANALOGUE BEAMFORMER WITH SINUSOIDAL CHARACTERISTIC

TOTAL Nº OF SAMPLES 1200
Nº OF COMPLETE WEIGHT SET UPDATES 60
Nº OF ELEMENTS PROCESSED ON EACH CLOCK CYCLE 2
DWELL TIME ON EACH ELEMENT(S) 10 SAMPLES
NUMBER OF ELEMENTS 5
ELEMENT SPACING IN WAVELENGTHS .5
NUMBER OF GAUSSIAN JAMMERS 3

JAMMER Nº1 OF POWER 0dB AT ANGLE 25°
JAMMER Nº2 OF POWER -10dB AT ANGLE 70°
JAMMER Nº3 OF POWER -20dB AT ANGLE -40°
THERMAL NOISE POWER (dB) -70
SINUSOIDAL WEIGHT CHARACTERISTIC
GAIN FACTOR .1

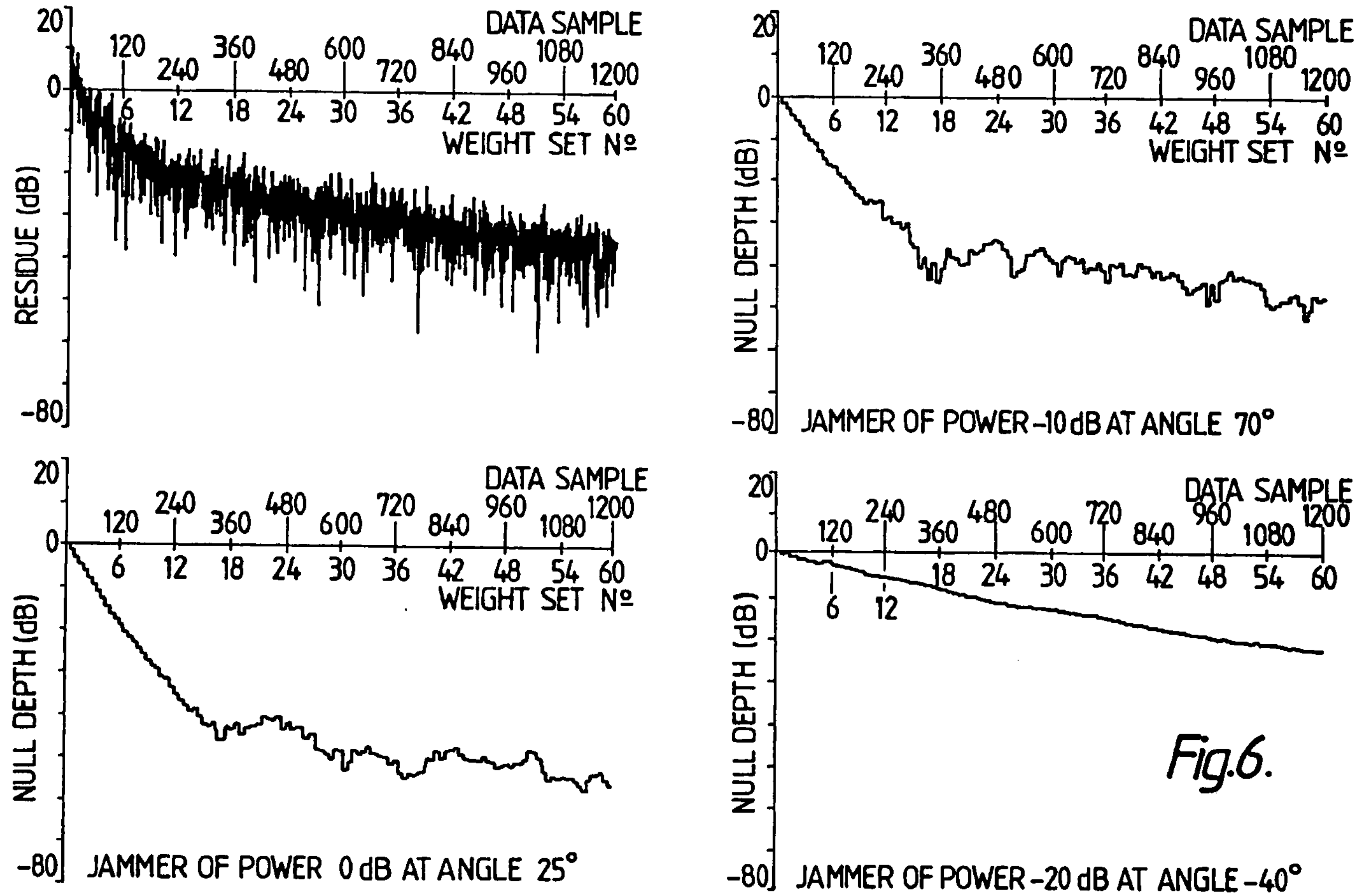

Fig.6.

TOTAL Nº OF SAMPLES 1200
Nº OF COMPLETE WEIGHT SET UPDATES 90
Nº OF ELEMENTS PROCESSED ON EACH CLOCK CYCLE 3
DWELL TIME ON EACH ELEMENT(S) 10 SAMPLES
NUMBER OF ELEMENTS 5
ELEMENT SPACING IN WAVELENGTHS .5
NUMBER OF GAUSSIAN JAMMERS 3

JAMMER Nº1 OF POWER 0dB AT ANGLE 25°
JAMMER Nº2 OF POWER -10dB AT ANGLE 70°
JAMMER Nº3 OF POWER -20dB AT ANGLE -40°
THERMAL NOISE POWER (dB) -70
SINUSOIDAL WEIGHT CHARACTERISTIC
GAIN FACTOR .1

COMPUTER SIMULATION DEMONSTRATING THE USE OF TIME SHARED QR WITH FEEDBACK TO CONTROL AN ANALOGUE BEAMFORMER WITH SINUSOIDAL CHARACTERISTIC

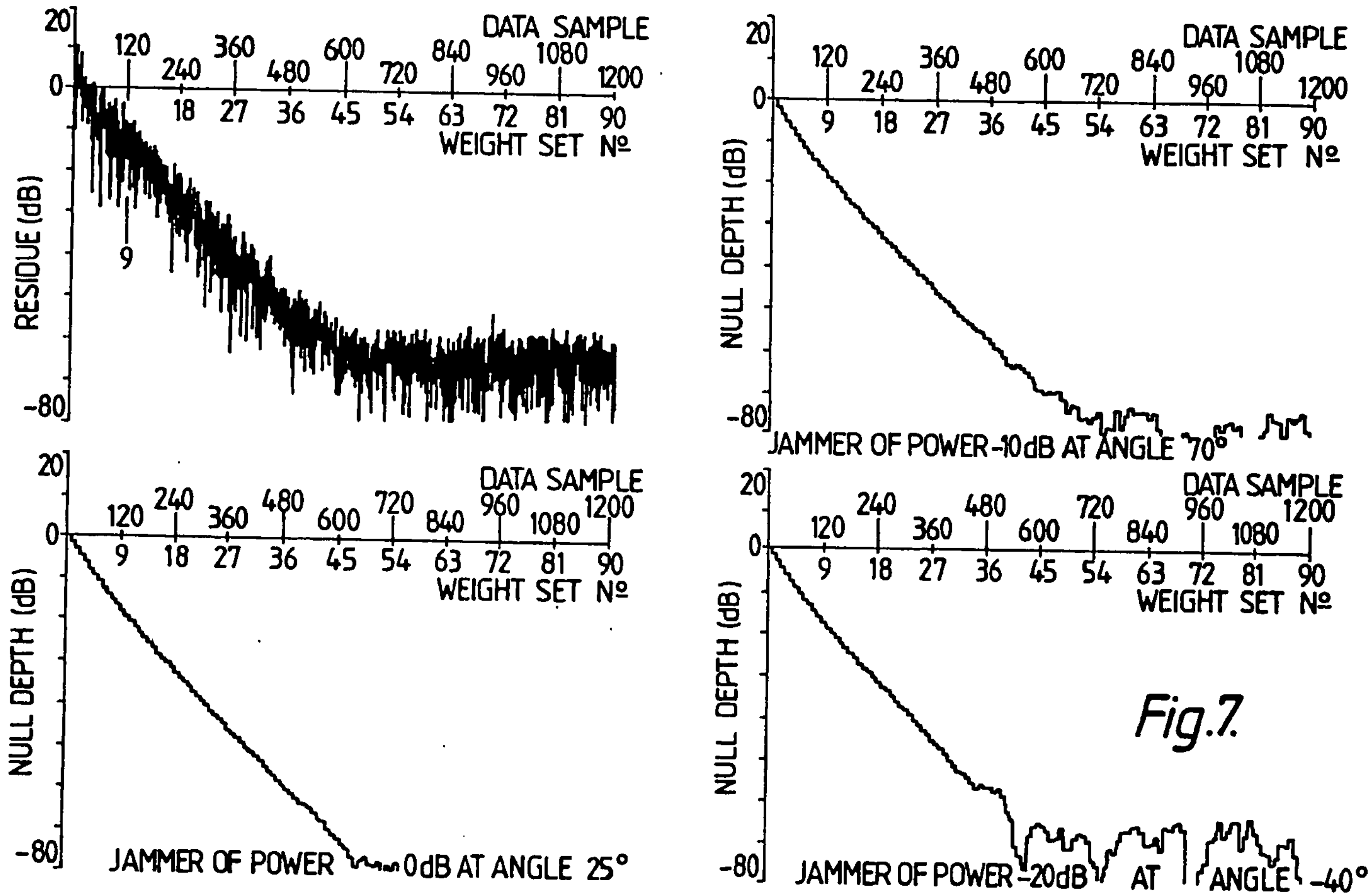

Fig.7.

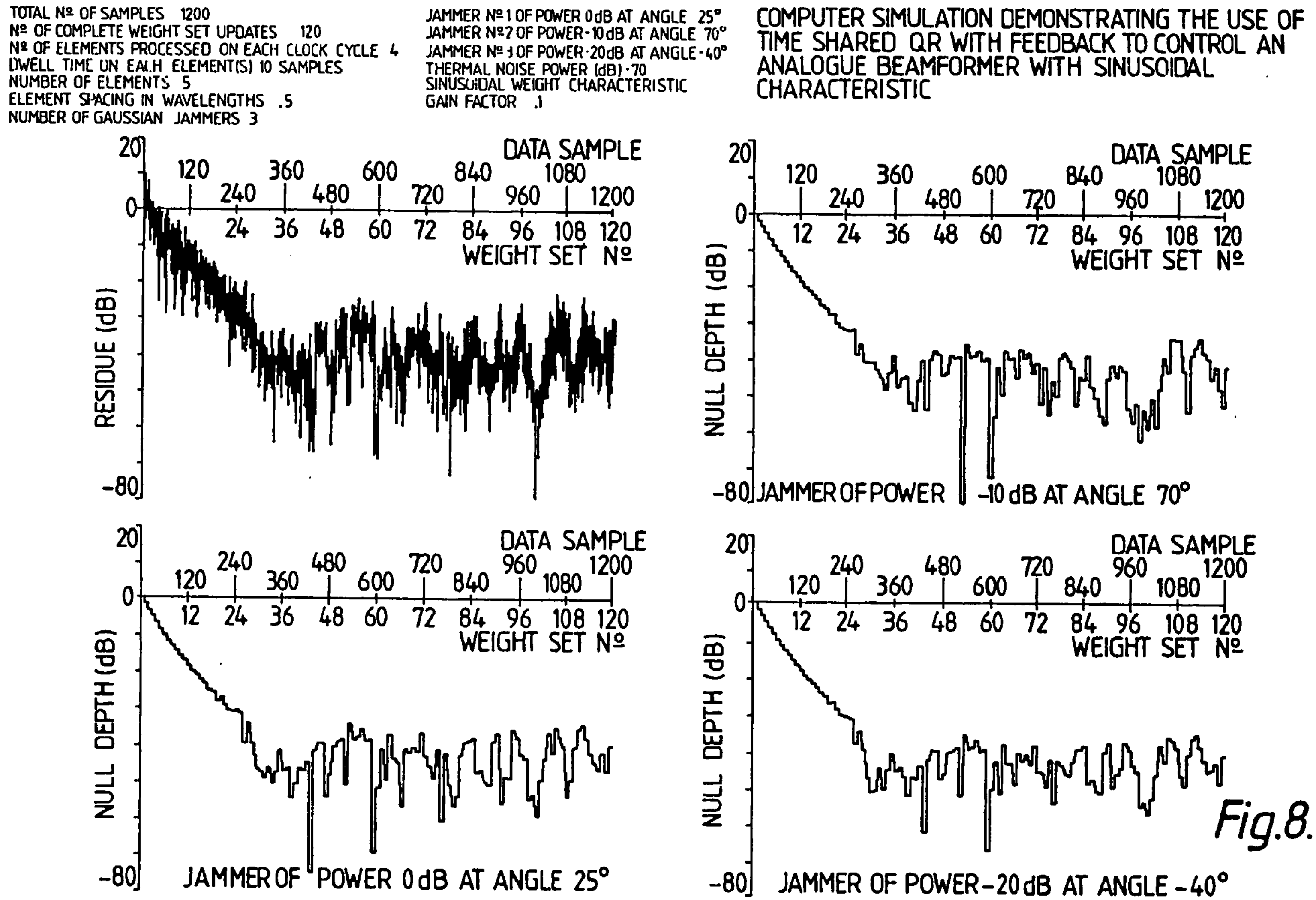
TOTAL Nº OF SAMPLES 1200
Nº OF COMPLETE WEIGHT SET UPDATES 120
Nº OF ELEMENTS PROCESSED ON EACH CLOCK CYCLE 4
DWELL TIME ON EACH ELEMENT(S) 10 SAMPLES
NUMBER OF ELEMENTS 5
ELEMENT SPACING IN WAVELENGTHS .5
NUMBER OF GAUSSIAN JAMMERS 3
JAMMER Nº1 OF POWER 0dB AT ANGLE 25°
JAMMER Nº2 OF POWER -10dB AT ANGLE 70°
JAMMER Nº3 OF POWER -20dB AT ANGLE -40°
THERMAL NOISE POWER (dB) -70
SINUSOIDAL WEIGHT CHARACTERISTIC
GAIN FACTOR .1
COMPUTER SIMULATION DEMONSTRATING THE USE OF TIME SHARED QR WITH FEEDBACK TO CONTROL AN ANALOGUE BEAMFORMER WITH SINUSOIDAL CHARACTERISTIC
DATA SAMPLE
WEIGHT SET Nº
RESIDUE (dB)
NULL DEPTH (dB)
JAMMER OF POWER 0dB AT ANGLE 25°
JAMMER OF POWER -10dB AT ANGLE 70°
JAMMER OF POWER -20dB AT ANGLE -40°

Fig.8.